i-Cassava Disease Classification

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Abstract

In Africa, the production of cassava is experiencing drastic reduction as a result of disease infections, climatic changes, agricultural practices to mention a few which poses treats its nutritional and economic values. With the use of deep learning techniques, this study aims at tackling cassava plant disease detection and classification in order to provide early detection of such and appropriate control measures in curbing their spread.

1 Introduction

Manihot Esculenta Cranz, popularly called Cassava is believed to have originated from South America, probably the Amazon region as it may have been the center of origin for species that gave rise to Manihot Esculenta. The 16th century marked the beginning era of cultivation cassava crops in the West Coast of Africa during the visitation of the Portuguese Brazilian to Africa. Its agricultural practices later spread to East Africa. Currently, Africa recorded the highest cassava production more than the rest of the world with Nigeria taking the lead of 35 percent of its total production and 19 percent of the world production [10].

As the cultivation of Cassava increased in Africa, so has the pest and disease that attack the crop. Research shows that over 30 diseases with causes ranging from virus to bacteria to fungi affect the crop which is one of the main challenges facing cassava production but most of the symptoms are visible [9].

Generally, cassava is second to sweet potato as the most important starchy root crop of the tropics [11] classified as sweet or bitter based on the quantity of cyanide compounds found in it [9]. Nevertheless, Cassava is largely consumed by many countries in Africa such as Sierra Leonne, Angola, Benin, Congo, etc as one of the most important staple foods since it is cheaper to grow and manage. Over the years, little research has been conducted on the crop until recently where it has gained much attention and can be seen as a crop that adjusts well with African conditions[8]. The most common diseases that affect cassava are known to be Cassava Brown Streak(CBSD) discovered in 1930 in Tanzania and caused by a virus believed to take after carlaviruses, Cassava Mosaic Disease (CMD) also believed to be part of potexvirus group first noticed in Brazil, Cassava Bacterial Blight (CBB) caused by Xanthomonas campestris pv. Manihotis and Cassava Green Mite (CGM) [7].

1.1 The Dataset

Being part of the crowdsourcing project by the Artificial Intelligence Lab at Makerere University and the National Crops Resources Research Institute, the collected data of 5 different classes consists of 9,436 labeled and 12,595 unlabeled images of cassava plant leaves. The training and testing labeled data have their class percentage distribution of 46.99%, 25.51%, 8.24%, 13.67% and 5.59% for Cassava Mosaic Disease (CMD), Cassava Brown Streak Disease (CBSD), Cassava Bacterial Blight (CBB), Cassava Green Mite (CGM), and Healthy respectively [1]. This revealed that the classes are unbalanced.

(a) Healthy (b) CBB (c) CGM (d) CBSD (e) CMD

2 Review of Related Work

The contributions of researchers in the field of artificial intelligence in automating the diagnosis of diseases affecting the agricultural crops – cutting down their production yield and drastically reducing their economic value have been gathering pace

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over the years. The light of this approach (the use of the deep neural network for image recognition and object detection) is aiding the early detection of crop diseases; which gives direction(s) of modern treatment and agricultural best practices in curing these diseases and curbing their spread in a cost-effective and technology scalable manner.

In sub-Saharan Africa, the deploration of transfer learning convolutional models in portable gadgets like mobile devices for the diagnosis of cowpea diseases has offered a reliable, cheap, and speedy way of digitalizing disease detection in plants with high accuracy Nsumba et al. [2]. The proposed detection models used Google's pre-trained InceptionNet since it requires less computational demand compared to training from scratch. The model performance of training its topmost layer of MobileNet with inception softmax layer achieved an overall accuracy of 93% in categorizing the detection of the studied cowpea plants as healthy, powdery mildew, Cercospora and mosaic virus. Doreen et al. [3] contributed to determining the infection level of Cercospora leaf spot diseases in cowpeas using OpenCV library and color-bob detection.

Aduwo et al. [4] made a notable laboratory experiment of uniform lighting and background to diagnosis the leaf images of cassava plant using computer vision by developing a two-class algorithm which extracts features (hue and intensity, key points of the area of interest and scale-invariant feature transformation and speeded-up robust features) for detecting the healthy status of the plants and their classification. Modification of their classification methods to a multi-class problem with multiple diseases and their severity stages have been considered Owomugisha et al. [5]. In addition, Owomugisha et al. [5] used spectrometry to capture the disease's underlying structure in the leaves before it becoming symptomatic which is a high dimensional spectral data for diagnosis compared to image data. This is an advanced method and requires a lot of computational resources compare to our adopted approach as used in [1].

Recently, Mwebaze et al. [1] approached the challenge of annotating or labeling of the healthy and unhealthy (associated with the most common cassava plant diseases being classified) status of cassava plants using semi-supervised learning. Since their approach also used the computer vision techniques, it seized the easiness of categorizing cassava plants without the extra cost for experts, checks of disease type, and its severity level in affected plants. The impact of their work is highly relevant in ensuring preventive measures for healthy cassava plants and the provision of treatments to the affected ones, thus, increasing the large scale production yield of cassava for food security and to the needy industries as raw materials.

As a contribution to improving the accuracy of the participating algorithms in [1], we partook in the 2nd Cassava Disease Challenge African Masters in Machine Intelligence (AMMI 2020) experimenting with the state-of-art deep learning architecture, tools, and techniques.

3 Experimentation and Result

Our experimentation approach is reported as follows:

3.1 Custom Residual Network Architecture

We used the Pytorch deep learning framework library to train the given dataset from scratch on custom-built residual networks with 3 and 12 stacked 2D-convolutional layers. During training, we set a batch size of 32 with scheduled learning rate decay after 25 epochs using the stochastic gradient descent (SGD) and adaptive momentum (Adam) as the optimizers. The 63.65% accuracy score obtained with the 3-layered network was set as a baseline score. The 12-layered network performed quite a bit better.

3.2 The ResNet Architecture

To improve on our existing baseline score, we chose to train all the layers of the ResNet18 architecture from scratch. Our accuracy only had 0.01% increment compare to our previous experiment. Intuitively, to leverage the computational advantage of transfer learning techniques, we used the pre-trained ResNet101 parameters fine-tuning its topmost layer to output the number of classes in our classification task.

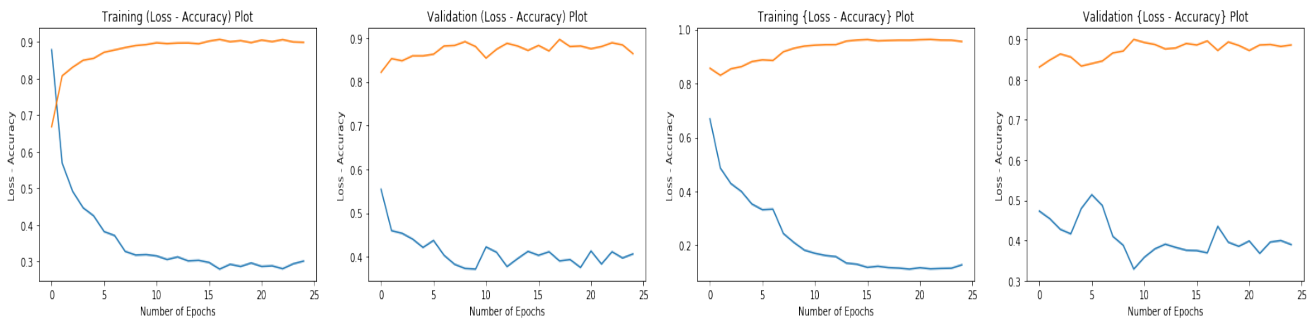
Table 1: Result summary of experimentation

-			-	Training		Validation	
Model	Parameter	Pre-trained	Epoch Cycle	Loss	Accuracy	Loss	Accuracy
Custom ResNet3	115K	False	25	1.0314	0.6365	1.0314	0.6365
Custom ResNet12	570K	False	25	0.9888	0.6295	0.9680	0.6663
ResNet18	11M	False	25	0.9646	0.6446	0.9245	0.6713
ResNet101	44.5M	True	25	0.2851	0.9034	0.4246	0.8725
ResNet101 extraimages	44.5M	True	15	0.364	0.8970	0.9680	0.6660
ResNet101*	44.5M	True	25	0.2107	0.9300	0.3282	0.9000
ResNet101* extraimages	44.5M	True	15	0.1893	0.9390	0.1705	0.9523
Vgg19	144M	True	25	0.2928	0.9003	0.3905	0.8962

* Model trained with Adam optimizer

However, there is a high chance of overfitting due to the model complexity as the number of the given labeled training data is small, hence the semi-supervised techniques of using the pre-trained model for the prediction of classes of the unlabeled extra-images in the dataset was taken. With a probability threshold of 0.95, the labeled extra-images were added to the given training dataset which enabled us to train on a larger dataset on ResNet101* for 15 epoch cycle scoring an overall of 0.364 validation loss score, and 89.70% accuracy score.

The table 1 gives the result summary of our experiments with the training and validation for vgg19 and ResNet101 without extra-images are given beneath.



4 Conclusion

In conclusion, based on our explored techniques, the ResNet101 architecture trained with Adam optimizer performed better compared with others. Although we had the highest validation accuracy score when trained with extra-images, this model performs worst on the predicted test dataset was submitted for validation on Kaggle. We believe the high accuracy recorded was as a result of biases introduced by training with extra-images.

5 Recommendation

We recommend finding better techniques to make use of extra-images to improve the training task and trying other techniques of model fine-tuning in transfer learning, as we only tried two methods of fine-tuning the out-most layers and re-training all the layers due to the limitation for computational power.

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